# Seizure Detection using EEG

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## 1 Introduction

Neonatal babies experience seizures due to reasons such as lack of oxygen, haemorrhage, meningitis, infection and stroke. Approximately one-third of these seizures are clinically visible and more than 90% of even these seizures go undetected; which can sometimes lead to brain damage and in severe cases, death [13].

In this project, we try to develop a classifier that works on multi-channel input to accurately classify EEG sequences into ictal (seizure segments) and interictal (non-seizure) segments. This would be extremely useful for clinicians in a neonatal intensive care unit to automatically detect seizures in babies and therefore take necessary remedial action.

## 2 Method

### 2.1 Dataset

Intracranial EEG data analyzed for this study was provided by the UPenn - Mayo Clinic Seizure Detection Challenge on kaggle.com, sponsored by the American Epilepsy Society, and the data is available via the NIH-sponsored International Epilepsy Electrophysiology Portal (ieeg.org) [2, 11]. The dataset corresponded to 8 patients and has segments specifically labelled as interictal or ictal. Ictal segments cover the entire seizure, while interictal segments cover approximately the mean seizure duration for each subject. Starting points for the interictal data segments were chosen randomly from the full data record, with the restriction that no interictal segment be less than one hour before or after a seizure. Each segment had input from multiple channels which varies per patient, however is the same for a given patient across all segments. Further understanding of the dataset can also be obtained from Table 1.

### 2.2 Classifier

An study of the various mechanisms for EEG signal based classification has already been done and has concluded that the SVM is better than most other known forms of classifiers [6]. This, and the popularity of the SVM based classifiers and the ease of use through tools like LibSVM [3, 9], we decided to use SVM in order to classify the data segments. A feature set of 21 was generated from

Table 1: Description of the dataset

| | Ictal | Interictal | Number of channels |
|---|---|---|---|
| **Patient 1** | 70 | 104 | 68 |
| **Patient 2** | 151 | 2990 | 16 |
| **Patient 3** | 327 | 714 | 55 |
| **Patient 4** | 20 | 190 | 72 |
| **Patient 5** | 135 | 2610 | 64 |
| **Patient 6** | 225 | 2772 | 30 |
| **Patient 7** | 282 | 3239 | 36 |
| **Patient 8** | 180 | 1710 | 16 |

each segment, normalised and used for training and prediction. The approach was similar to the one that has already been proposed in literature [7, 13] with slight variations which would simplify the prediction model and save computation time, thus allowing the patient to receive real-time assistance.

## 2.3 Feature Extraction

Before we extracted features, each EEG sample was first downsampled to 256 Hz and then each channel's data was band-passed through a Chebyshev Type II filter in the range 0.5-34 Hz [7]. A set of 21 features was then extracted and used to train the SVM [7, 13]. These features were taken from all possible domains - time, frequency and entropy. After calculating the feature values channel-wise for all the data segments, the mean of the values across channels was taken and was used to represent the segment in all further analysis. Note that this is a *significant departure* from literature where all channels are individually considered and should lead to quicker classification.

### 2.3.1 Time domain features

In the discussion below, $N_S$ is the number of points at which we have the value of the signal.

1. *Line length*: Curve length - an estimate of the fractal dimension is a proposed feature in adult epileptic seizure detection and is used here.

$$L = \sum_{k=1}^{N_S} |x(k) - x(k-1)|$$

2. *RMS Amplitude*: Mannual detection of neonatal seizures takes place through an amplitude integrated EEG in the ICU. Thus, the RMS amplitude is taken as a feature.

$$A = \sqrt{\frac{1}{N_S} \sum_{k=1}^{N_S} x^2(k)}$$

3. *Zero Crossings*: The number of zero crossings is thought to change during a seizure and is therefore taken as a feature in this study. It is calculated by counting the number of times

$$x(k) \cdot x(k+1) < 0$$

4. *Minima and Maxima*: The number of local maxima and minima in a data segment is used as a feature and is calculated by counting the number of times that the first derivative of the signal is less than $\varepsilon$ $(= 1)$

5. *Nonlinear energy*: This is a feature that is commonly used in seizure detection in adults. The mean non-linear energy is taken as a feature.

$$N(k) = x^2(k) - x(k-1) \cdot x(k+1)$$

6. *Hijorth parameters*: These are simple statistical measures on the EEG signals and have been extensively used in seizure detection.

   - *Activity*: This is the variance of the signal amplitude $\sigma_x^2$
   - *Mobility*: This can be expressed as the following equation

$$\delta_x = \frac{\sigma_{x'}}{\sigma_x}$$

   - *Complexity*: This can be expressed as the following equation

$$\lambda_x = \frac{\sigma_{x''}/\sigma_{x'}}{\sigma_{x'}/\sigma_x}$$

7. *Autoregressive Model Fit*: The wide usage of the AR model methods in EEG classification motivated us to use this as a feature. We used the modified covariance method to obtain a $7^{th}$ order model and calculated the error in the fit as a feature [4].

### 2.3.2 Frequency domain features

1. *Bandwidth (BW)*: The bandwidth is defined as the width in hertz between the two half power points of the dominant spectral peak.

2. *Peak Frequency*: The peak frequency was defined to be the frequency in the power spectral density with the largest average power in its bandwidth.

3. *Peak Power*: Peak power is the maximum power attained in the periodogram estimate of power spectral density of the signal.

4. *Spectral Edge Frequency (SEF)*: Spectral edge frequecy is the frequency below which 90% of the total power resides.

5. *Total Spectral Power (TP)*: As the name suggests, it is the sum of the spectral power over the frequency range 2-20Hz.

6. *Intensity Weighted Mean Frequency (IWMF)*: The IWMF is a weighted mean of the frequencies present in the power spectral density estimate. It is given by the following expression.

$$IWMF = \frac{\sum_{i=1}^{N_f/2-1} p_i i df}{\sum_{i=1}^{N_f/2-1} p_i}$$

   here $i$ is the frequency bin number, $p_i$ is the estimated power spectral power in bin $i$ and $df$ is ratio of sampling rate to total number of frequency bins.

7. *Intensity Weighted Bandwidth (IWBW)*: Similar to IWMF, this can be expressed as following:

$$IWBW = \sqrt{\frac{\sum_{i=1}^{N_f/2-1} p_i (IWMF - idf)^2}{\sum_{i=1}^{N_f/2-1} p_i}}$$

8. *Wavelet Energy*: For our analysis, the fifth level wavelet coefficient, decomposed through 8 levels, was used as the wavelet energy for each epoch [5, 12].

#### 2.3.3 Entropy domain features

Seizure activity is thought to represent a drop in the complexity of the underlying brain dynamics, which motivates the usage of entropy domain features for analysis.

1. *Spectral Entropy ($H_S$)*: Spectral entropy has been regularly used for detection of adult seizures.

$$H_S(X) = -\frac{1}{\log N_f} \sum_f P_f(X) \log P_f(X)$$

   where $P_f(X)$ is calculated by normalising the PSD with the total power [8].

2. *Shannon Entropy ($H_{SH}$)*: A histogram estimate of probability density $P_h(X)$ leads to Shannon entropy

$$H_{SH}(X) = -\sum_f P_h(X) \log P_h(X)$$

3. *Approximate Entropy ($H_{AP}$)*: This is a related measure, based on estimates of the behaviour of nonlinear dynamical components of the EEG. For this calculation we used code available online [1].

4. *SVD Entropy ($H_{SVD}$)*: Instead of calculating on the spectrum, when a similar process is performed on the SVD of the embedded matrix [10], the SVD entropy is obtained and is used as a feature.

### 2.4 Testing paradigm

The data was normalised to make it zero mean and unit variance before any analysis was done. Parameter tuning was performed via a grid search for the values of C and $\gamma$ in an SVM using the RBF Kernel function - $e^{-\gamma|x-y|^2}$. We used an iterative validation and testing technique to normalise the result for data related errors. In each iteration, we trained on 6 patients, validated and performed parameter tuning using the $7^{th}$ patient and tested on the $8^{th}$ patient, having trained the SVM on the first 7 patients. This is to mimic real life clinical analysis wherein the data for a patient would all come at once and we would have to do real time identification of seizure events.

Table 2: Summary of results obtained

| | Precision | Recall | F-measure | Accuracy |
|---|---|---|---|---|
| **train = {1,2,3,4,5,6} validate = {7} test = {8}** | 0.6484 | 0.6556 | 0.6519 | 65.0000% |
| **train = {2,3,4,5,6,7} validate = {8} test = {1}** | 0.9091 | 0.5714 | 0.7018 | 75.7143% |
| **train = {3,4,5,6,7,8} validate = {1} test = {2}** | 0.9704 | 0.8675 | 0.9161 | 92.0530% |
| **train = {4,5,6,7,8,1} validate = {2} test = {3}** | 0.5617 | 0.6820 | 0.6160 | 57.4924% |
| **train = {5,6,7,8,1,2} validate = {3} test = {4}** | 0.6190 | 0.6500 | 0.6341 | 62.5000% |
| **train = {6,7,8,1,2,3} validate = {4} test = {5}** | 0.6148 | 0.5556 | 0.5837 | 60.3704% |
| **train = {7,8,1,2,3,4} validate = {5} test = {6}** | 0.7807 | 0.7911 | 0.7859 | 78.4444% |
| **train = {8,1,2,3,4,5} validate = {6} test = {7}** | 0.6850 | 0.7943 | 0.7356 | 71.4539% |

# 3 Results

Table 2 shows a summary of the results obtained through our testing paradigm. As can be seen, in addition to the accuracy, we have also reported the precision, recall and f-measure for each case [14]. Precision is the ratio of true positives to the total number of positives returned by the classifier; recall is the ratio of ictal segments identified by the classifier from amongst all ictal segments and F-measure is the harmonic mean of the precision and recall. A shorter summary of the results is as follows:

`Mean Precision` - 0.7236
`Mean Recall` - 0.6959
`Mean F-measure` - 0.7031
`Mean Accuracy` - 70.3785%

The interesting thing about these results is that the precision, recall and accuracy are comparable and therefore this shows that the model is definitely unbiased.

# 4 Conclusions

We note that although some implementations of the classifiers claim to have achieved very high accuracy, they consider multiple channels and take all of them into consideration while computing the features. In this work, we have explored the effeect of taking the mean value of the features and predicting. We observe that this leads to a significant improvement in accuracy over the manual inspection method traditionally used in clinics and at the same time,

by taking the mean instead of computing on all channels (as shown in Table 1), it provides significant gains in time spent on computations for classification.

It is also seen that the accuracy obtained is greatest when we train with large number of ictal segments (Refer Tables 1 and 2). Therefore, it can be said that the method will potentially perform well if presented with more data and when it has more data points for generalisation. The lack of ictal (the class we are more interested in) probably leads to an overfitting on the dataset that we have and therefore exploration of the performance when more data is available should form a part of future studies in this area.

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